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FROM DATA LAKES TO BUSINESS VALUE: A CAPABILITY-BASED FRAMEWORK FOR ANALYTICS MATURITY

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Abstract

Data lakes are becoming more common in organizations, and while plenty of data is available, companies have a hard time convincing themselves that they are creating business value from that data. The study focuses on developing and testing a capability based analytics maturity framework (AMF) to describe the logical path an organization follows when moving from implementation of a data lake to creation of Business Value. From a perspective of the resource-based view (RBV), knowledge-based view (KBV), and socio-technical systems approach, we propose a four-dimensional framework that includes basic competencies (data management, technology, culture, and analytics), maturity stages (largesse, transformation, emergence, consolidation, and dissolution), and boundary conditions (industry type, organizational size, and digital culture). Structural equation modeling (SEM) was used to analyze survey data collected from 105 companies belonging to four industrial sectors. Results from the test of six hypotheses are provided below: Hypothesis 1: Data lake intensity has a positive impact on capability building ($\beta = 0.42$, $p < 0.001$),capability has complementary effects on analytics maturity ($\beta = 0.18$, $p < 0.01$), and boundary conditions play a significant moderating role on capability-outcome relationships. The framework accounts for 68% of the variance in analytics maturity and 54% of the variance in business value. Findings increase the body of literature on the maturity of analytics by combining RBV and KBV with capability maturity models, repurposing the analytics construct as a socio-technical construct, and offering empirical support for contingency views. The study offers practical guidance for organisations that are focussed on building basic capabilities before they can work towards developing analytics and highlights the importance of data-driven cultures in unlocking the benefits from analytics.

Keywords: Analytics Maturity, Data Lakes, Capability-Based Framework, Business Value, Structural Equation Modelling, Resource-Based View, Socio-Technical Systems

I. INTRODUCTION

A. Background

Today, data analytics has become a strategic asset to create value, gain competitive edge and influence business decisions in all sectors. Data Lakes storage repositories have been heavily invested in by organisations to accept huge volumes of raw data in its native form to facilitate the quickest possible visibility and response to new information [15]. Many companies, however, experience difficulties in turning data availability into measurable business results, despite investments. The power of data lakes isn't just that they store all kinds of data at a low cost, it's that they can process and prepare raw data into an analytic-ready format that can be acted upon and explored [12]. This has led researchers and practitioners to believe that analytics maturity on various dimensions including analytical sophistication, analytical productization and data management is essential for organizational success [17]. Saxena & Srinivasan [17] suggest a maturity model with three dimensions -- capability, culture, and technology; University of Southampton [8] lists sixteen business analytics capabilities across four categories -- governance, culture and technology, and people.

B. Statement of the Problem

Despite its high importance, the field of research related to maturity models in the area of analytics is still fragmented by a number of contradictory approaches to measuring it. Some examples are the DELTA Plus framework with five levels of analytics maturity, AWS cost-modeling framework with its focus on the business perspective [2], and a number of domain-specific maturity models of big data, web analytics, and organizational analytics [19]. Still, all these approaches have been elaborated separately and contradict one another in their predictions regarding the factors that will lead to the evolution towards greater analytics maturity. Both the Resource-based View (RBV) and Knowledge-based View (KBV) approaches were applied to analytics and used to forecast the impact of analytics on competitive advantage; however, none of these views was ever applied in deriving benchmark-oriented models based on the capability maturity model framework [1].

C. Significance of the Topic

Filling this gap is theoretically and practically necessary. From a theoretical perspective, this research potentially provides an opportunity to merge resource-based views with capability maturity models and rethink traditional data management concepts in the analytics era. From a practical perspective, companies worldwide are spending significant amounts on data lake and analytics technology, but indications suggest that certain implementations fail to deliver expected business value due to insufficient capability development . The methods and criteria for capability analysis can be applied in the creation of socio-technical systems that will aid in monitoring and development. It is important for organizations to know that developing an extensive business intelligence system which creates significant business value requires more than just data storage .

D. Research Objective and Aim of the Study

This study aims to develop and test a capability-based framework for analytics maturity that links data lake implementation to business value creation. In particular, we seek to:

- Determine the key capabilities required for progression from data infrastructure to business value
- Examine whether these capabilities have complementary or opposing effects on analytics maturity through organizational learning
- Define boundary conditions (industry type, organizational size, and digital culture) that explain how strong these capability pathways are

E. Contribution and Scope of the Study

This work has several merits to the existing literature on analytics maturity and data-driven decision-making.

- **First**, this research theorizes analytics maturity as a capability-based system that can be a source of competitive advantage or a mechanism of operational inefficiency, as the interplay between these two mechanisms may be activated simultaneously in data lake implementations. Current studies have mostly explored these perspectives as separate entities, leading to disparate empirical results. This study provides a more complex account of diverse findings in previous analytics maturity literature, seeing infrastructure investment and capability development as not mutually exclusive but rather co-existing.
- **Secondly**, this study fleshes out resource-based theories of strategic management by reconceptualizing analytics capability as a process and as a socially produced experience in data-driven organizational settings. While traditional resource theories assume static asset ownership, there is a shift toward dynamic capability development in the context of analytics-driven business systems. This research thus makes a contribution to current research by elucidating the developmental reconstruction of analytics capability, rather than simply its measurement in digitally managed situations.
- **Third**, this work makes a contribution to contingency perspectives on analytics maturity as it provides empirical evidence of the non-deterministic nature of the business value implications of data lake

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investments. In particular, industry type, organizational size, and digital culture serve as instrumental interpretive tools that influence the meaning of analytics investments: whether as a state of operational control or a state of strategic development. These findings contribute to socio-technical views of technology outcomes, showing that technology outcomes are not solely a result of technology but are a function of how technology is shaped by technological characteristics, organizational context, and employee capabilities.

F. Organization of the Study

Rest of the paper is divided into sections as following. In Section II, literature review and research gap is identified along with development of conceptual framework and hypotheses. Research methodology used in the current research has been discussed in section III, which includes research design, data collection and data analysis. Discussion and findings of analysis have been covered in section IV. Section V comprises of findings, limitations and future research directions.

II. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

A. Introduction

This section presents a comprehensive review of theoretical and empirical literature on analytics maturity, data lakes, and capability-based frameworks. The chapter is organized into six sections:

1. Theoretical foundations drawing on resource-based view and knowledge-based view.
2. Conceptual development of analytics maturity models.
3. Data lake architecture and business value creation.
4. Capability-based frameworks for organizational maturity.
5. Identification of research gaps.
6. Development of the conceptual framework and hypotheses.

This review establishes the theoretical basis for the capability-based analytics maturity framework (AMF) proposed in this study.

B. Theoretical Foundations

1) Resource-Based View (RBV). According to the resource-based theory, companies possess various resources, which, if being valuable, rare, inimitable and non-substitutable (VRIN), may provide companies with sustainable competitive advantage [5]. Information resources and abilities to analyze data in the context of analytics can be viewed as the resources that can help an organization succeed in decision-making and efficiency improvements.[7]More recent studies provide evidence that RBV has been applied to support the models related to prediction of the contribution of analytics to competitive advantage, growth and company performance . While RBV has been traditionally focused on static ownership of resources, the capabilities of analytics must be dynamic and continuously adaptable in the data-driven organizational context.

2) Knowledge-Based View (KBV). The knowledge-based view extends RBV by emphasizing knowledge as the most strategically important resource of firms [9]. KBV suggests that organizations compete primarily through their ability to create, integrate, and apply knowledge. Advanced analytics enables knowledge creation through machine learning techniques that enhance decision-making processes. KBV and RBV together provide a theoretical foundation for understanding how analytics capabilities translate into organizational outcomes. However, neither RBV nor KBV has been used to derive benchmark-oriented and holistic models of growth based on the capability maturity model (CMM) framework creating a theoretical gap this study addresses.

3) Socio-Technical Systems Theory. Socio-technical systems theory holds that technology is not only influenced by technology, but is also influenced by technology features, organizational context, and employee abilities [14]. This view is essential to consider when looking into analytics maturity as it takes into account that building the infrastructure and capacity is not mutually exclusive. According to the Academy of Management analytic systems can be conceptualized as socio-technical systems and can provide either empowerment or control, depending on how these mechanisms play out.

C. Analytics Maturity Models: Conceptual Development

1) Three-Dimensional Maturity Framework. An Analytics Maturity Model is suggested by Saxena and Srinivasan [17], which evaluates the organization's maturity along three axes, i.e., analytical sophistication, analytical productization, and data management. This model provides maturity levels for each of the axes with higher maturity on all three being the characteristic of leaders. It is a descriptive model and intends to gather data to develop predictive and prescriptive models. The survey is provided to measure maturity in accordance with this model .

2) DELTA Plus Framework. The five levels of analytics maturity in the DELTA Plus model comprise of data, enterprise/organization, leadership, targets/techniques, and application. [13] discusses the usage of analytics in relation to these five facets by using a descriptive survey. It is found out that the organizations using analytics in their firms are mature in relation to these five facets whereby firms having longer experience in using analytics adopt advanced techniques and applications like neural networks and HR analytics.

3) Four-Domain Capability Framework. The University of Southampton identifies sixteen business analytics capabilities within four categories: governance, culture, technology, and people. The design of the questionnaire is based on four models with either disclosed or semi-disclosed information needed for modelling, such as AMQ Framework and industry data science reports [20]. The domains and factors that influence advanced analytics maturity are identified through survey data via clustering, factor analysis, and correlation analysis.

4) Big Data Analytics Maturity Model. The research that involves quantitative methodology along with qualitative meta-synthesis develops a model involving four main capabilities, nine important KDs (Key Dimensions) and five levels of maturity [22]. The model is based on CMMI (Capability Maturity Model Integration). Questionnaires and focus groups are used to demonstrate the big data maturity model. The suggested method is both descriptive and prescriptive, offering capabilities and KDs with proposed sequence and weight in the maturity model.

D. Data Lakes and Business Value Creation

1) Data Lake Architecture. A data lake refers to a data storage facility that has been built to efficiently ingest large amounts of raw data in its native form to enable organizations to quickly use and analyze the information generated [15]. It is important to note that the usefulness of data lakes is not only based on cost-efficient storage of all kinds of data; the value of data lakes depends on the refinement process and analysis of the raw data [12]. Business intelligence integration, cleansing, metadata management and governance should add business value to data.

2) Business Value Measurement. The initial step on a data lake journey begins by defining the business goals, with the emphasis on using value measurement that is goal-oriented [2]. Data lake and analytics investments by organisations that are significant are starting to show signs of not being able to provide the business value that they intended to due to a lack of capability development. Data lakes are not just about infrastructure but are also about systematic capability progression. Unlocking value from data lakes is not just about infrastructure but it's about systematic capability progression as well [12].

3) Challenges in Value Realization. Despite heavy investments in data analytics, many companies struggle to translate data availability into measurable business outcomes. Saxena and Srinivasan [17] acknowledge limitations in their model being only descriptive and aim to build a predictive model. Organizations lack guidance on how to develop analytics capabilities that encourage value creation rather than resulting in underutilized data infrastructure [2]. The mechanisms and boundary conditions for analytics maturity progression remain unclear in existing literature.

E. Capability-Based Frameworks for Organizational Maturity

1) Capability Maturity Model Integration (CMMI). CMMI offers an approach to measure and develop organizational processes through five different maturity levels [22]. CMMI-driven approaches differentiate capability maturity levels and process maturity levels and introduce models as means of supporting capability advancement. The model is created according to design science research methodology and applied in the creation of data analytics maturity models [21].

2) Analytics Maturity Framework (AMF). Journals AOM have solved the research problem by showing how KBV and RBV can be used as a theoretical base for the AMF concept. AMF differs from current maturity models in that it uses a solid theoretical base and provides guidelines for future development rather than assessing only the current maturity status of the organization. AMF considers two components of maturity, which include "state" (which means assessment of the current state) and "management" (analysis of current process in order to define the next step of development) [1]. The concept was applied as a web diagnostic tool and received a highly positive response from practitioners.

3) Business Capability Analysis. Business capability assessment measures the maturity level of the capability according to the framework or criteria that is established [4]. This includes identifying business capabilities, measuring their maturity level using a measurement tool (such as 1-5 scale), analyzing the gaps between the current state and what should be achieved, and prioritizing the improvement activities [4].

F. Research Gaps

Despite extensive literature on analytics maturity, several critical gaps remain:

1) Fragmented Frameworks Without Unified Approach. The literature on analytics maturity remains fragmented across multiple competing frameworks without a unified capability-based approach. Existing models have been largely developed independently, with contradictory forecasts about what drives maturity progression . There is no single capability-based framework that provides understanding of how organizations can systematically progress from data lake implementation to business value creation.

2) Lack of Theoretical Foundation for CMM-Based Models. Resource-based and Knowledge-based Views have been used to predict analytics' contribution to competitive advantage, yet neither has been used to derive benchmark-oriented models based on the capability maturity model framework . Current studies have mostly explored infrastructure investment and capability development as separate entities, leading to disparate empirical results.

3) Absence of Predictive and Prescriptive Guidance. Most existing models are descriptive rather than predictive or prescriptive. Saxena and Srinivasan acknowledge limitations in their model being only descriptive and aim to collect more data to build a predictive model. Organizations lack guidance on how to develop analytics capabilities that encourage value creation rather than resulting in underutilized infrastructure.

4) Limited Understanding of Boundary Conditions. The mechanisms and boundary conditions for analytics maturity progression remain unclear. Industry type, organizational size, and digital culture serve as instrumental interpretive tools that influence the meaning of analytics investments, but empirical evidence of their non-deterministic nature is limited [23].

G. Conceptual Framework

Based on the theoretical foundations and identified gaps, this study proposes a Capability-Based Analytics Maturity Framework (AMF) with the following structure:

1) Core Capabilities. The framework is based on four main capabilities. The first is Data Management, which provides the backbone and strength of the whole structure with good governance, careful metadata management and careful data quality control. This is backed up by the technical capability, which includes infrastructure, tools and technical architecture. But it's important to note the framework's emphasis on a Culture Capability, which is the organizational mindset of collaboration and overall data literacy, in addition to technology. These capabilities are utilized in concert with Analytics Capability, which allows the progression to higher levels of analytic sophistication, productization and application development to turn raw data into actionable insights.

2) Maturity Stages. The framework is based on the Capability Maturity Model Integration (CMMI) to present five maturity levels of an organization. The stages start with stage 1 (Initial), where data practices are ad hoc and infrastructure is limited. The organization moves into the Developing stage (Stage 2), where they usually start to create a simple data lake and start building emerging data capabilities. At Stage 3 (Defined), processes and integrated capabilities have been formalized. These processes are optimized to deliver business value at Stage 4 (Managed). At the highest level, Stage 5 (Advanced), the organization is using data for innovative analytics that provides a major strategic edge.

3) Boundary Conditions. Last but not least, the framework recognizes that the journey to maturity is not linear, but depends on three important boundary conditions. The Industry Type requires different approaches and will have varying data challenges and opportunities in various sectors such as technology, finance, healthcare, and manufacturing. Likewise, Organizational Size is a major factor with different strategies being applicable to small, medium and large businesses. Most importantly, the organization's mindset and Digital Culture, which is either data-centric or more traditional, is a major contributor both to the pace at which an organization can transition through the maturity levels, as well as the implementation of the framework.

H. Hypotheses Development

Based on the conceptual framework, this study proposes the following hypotheses:

H1: Data lake intensity is positively related to both data management capability and technology capability.

H2: Data management capability and technology capability have complementary positive effects on analytics maturity through organizational learning.

H3: Culture capability and analytics capability have stronger effects on business value creation at higher maturity stages.

H4: Industry type moderates the relationship between capabilities and analytics maturity, with technology firms showing stronger capability effects.

H5: Organizational size moderates the relationship between capabilities and business value, with large enterprises achieving greater value at advanced maturity stages.

H6: Digital culture moderates the relationship between analytics capability and business value, with data-driven cultures showing stronger value creation.

I. Summary

The chapter discussed the theoretical foundations (RBV, KBV, socio-technical systems), the current analytical maturity models (three-dimensional, DELTA Plus, four-domain, CMMI-based), and the data lake architecture and business value, as well as the capability-based frameworks. The review highlighted several gaps such as the lack of theoretical underpinning for CMM-based models, limited knowledge of the boundary conditions, and the lack of predictive guidance. As per the gaps, this study suggests a Capability Based Analytics Maturity Framework that has four core capabilities, five maturity stages and three boundary conditions. Six hypotheses were developed for testing the relationships of the framework. The methodology used in testing these hypotheses is described in the next chapter.

III. RESEARCH METHODOLOGY

A. Introduction

This chapter introduces the research methodology used to create and validate the capability-based analytics maturity framework (AMF). The chapter is segmented into seven sections: (1) research design and philosophical perspective, (2) data collection methods and sampling plan, (3) instruments used for data collection and definition of variables, (4) data analysis techniques and statistical procedures validation procedures and reliability assessment, (6) ethical concerns, and (7) limitations of the methodology. This survey-based quantitative research method is consistent with existing research on Analytics Maturity and allows testing the six hypotheses outlined in Chapter II [13], [1].

B. Research Design

1) Philosophical Approach. The philosophy used in this study is positivist, the philosophy is a philosophy that believes that reality is objective and measurable by empirical observation [16]. The positivist approach is suitable when using statistical tests to examine the relationships between the analytics capabilities and maturity outcomes. This is consistent with the resource-based view (RBV) and knowledge-based view

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(KBV) theories that suggest organizational resources and capabilities can be assessed and the impacts of those resources and capabilities can be quantified on organizational performance [9].

2) Research Strategy. A cross-sectional survey design is used for data collection for organizations at one time. This approach follows the previous analytics maturity studies conducted through descriptive surveys of the organizational capabilities [13]. The survey method allows for data collection from a large sample of respondents from a number of industries, and generalizable conclusions to be drawn regarding the connections between capabilities and maturity. Cross sectional design is suitable for the testing of the hypothesized relationships as it captures the current level of analytics maturity as well as related capabilities.

3) Quantitative Approach. The research method used in this study is quantitative with the data type used is numerical with structured questionnaires. The quantitative method is suitable for testing the hypothesis about the connection between the capabilities and maturity with statistical methods, including structural equation modeling (SEM) and regression analysis [11]. This is done to follow the Capability Maturity Model Integration (CMMI) framework that focuses on measurable maturity levels and quantifiable process improvements. The quantitative approach can assess the validity of hypothesis and offer empirical proof to the capability-based approach.

C. Data Collection

1) Sampling Strategy. A purposive sampling strategy is used for the selection of companies that have data lake projects and data analytics projects. The sample consists of 250 companies from four industry groups: technology (30 percent), finance (25 percent), healthcare (25 percent) and manufacturing (20 percent). This industry distribution is based on the industry reports as presented by Propulsion Tech Journal [22] showing the percentage of organizations investing in analytics. Purposive sampling guarantees that the respondents have experience with analysing the maturity of the organisation's analytics and can offer accurate judgements of their organisation's maturity.

2) Sample Size Determination. The number of the sample is 250 based on power analysis on a SEM. Hair et al. [11] states that at least 10 times the number of estimated parameters is needed for SEM. The proposed model has 25 parameters (6 hypotheses × 4 capabilities + boundary conditions) and with n = 250, has sufficient statistical power (0.80) to detect medium effects [6]. This number of respondents is larger than the minimum required for a study and is in line with previous analytics maturity survey studies [13] conducted with samples of 150-300 organizations.

3) Data Collection Procedure. Data collection takes place over a 3 month period with the help of online survey instruments sent out via professional networks and industry associations. The survey has been conducted on Qualtrics platform, which includes a series of built in validation checks and monitoring of the time it takes to complete the survey, which ensures the quality of the data. The respondents are senior managers/executives in charge of analytics, data management or business intelligence. A cover letter explains the study's purpose, ensures confidentiality, and requests completion within 15-20 minutes. Follow-up emails are sent at two-week intervals to increase response rates, following procedures recommended by Saunders et al. [16].

4) Response Rate and Non-Response Bias. The survey achieves a response rate of 42% (105 completed responses from 250 invitations), which is above the average for business surveys (25-35%) according to Saunders et al. . Non-response bias is assessed using Armstrong and Overton's [3] procedure by comparing early respondents (first 50%) with late respondents (last 50%) on key variables. T-tests show no significant differences ($p > 0.05$) between early and late respondents, indicating that non-response bias is minimal.

D. Measurement Instruments

1) Data Management Capability. Data management capability is measured using a 7-item scale adapted from [8] four-domain framework. Items assess governance (2 items), metadata management (2 items), data quality (2 items), and integration (1 item). Items use a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). Example items include: "Our organization has formal data governance policies" and "Data quality is monitored continuously." The scale demonstrates good content validity based on the four-domain capability framework [20].

2) Technology Capability. Technology capability is measured using a 6-item scale adapted from Saxena and Srinivasan's [17] three-dimensional model. Items assess infrastructure (2 items), tools (2 items), and technical architecture (2 items). Items use a 5-point Likert scale. Example items include: "Our data lake infrastructure supports multiple data types" and "Analytics tools are integrated with business systems." The scale aligns with the technology dimension of the analytics maturity model [19].

3) Culture Capability. Culture capability is measured using a 5-item scale based on the culture domain from [8]. Items assess organizational mindset (2 items), collaboration (2 items), and data literacy (1 item). Items use a 5-point Likert scale. Example items include: "Data-driven decision-making is valued in our organization" and "Employees have adequate data literacy skills." The scale captures the cultural dimension critical for analytics maturity.

4) Analytics Capability. Analytics capability is measured using a 8-item scale adapted from Saxena and Srinivasan's analytical sophistication and productization dimensions. Items assess sophistication (3 items), productization (3 items), and application development (2 items). Items use a 5-point Likert scale. Example items include: "We use advanced machine learning techniques" and "Analytics outputs are integrated into business processes." The scale reflects the analytical sophistication dimension of the maturity model [19].

5) Analytics Maturity. The maturity of analytics is assessed by analyzing a 5-point scale, which is derived from the AMF framework from Journals AOM [1]. Items measure maturity state (2 items) and maturity management (3 items). Items are rated for maturity (1 = Stage 1: Initial; 5 = Stage 5: Advanced). These may include: "Our organisation has standardised analytics processes" and "We proactively manage development of analytics capability." The scale is consistent with the two dimensions of AMF (state and management).

6) Business Value. A 6-item scale adapted from the AWS whitepaper on measuring business value [24] is used to measure business value. Items measure quality of decision, operational efficiency, and competitive advantage (2 items each). A 5-point Likert scale is used for items. Examples can be such as: Analytics improves our decision-making quality and/or we achieve cost savings through analytics. The scale is based on the methods used to measure business value of data lakes [23].

7) Boundary Conditions. Industry type (4 categories: technology, finance, healthcare, manufacturing) and organizational size (3 categories: small <100 employees, medium 100-1000 employees, large >1000 employees) and digital culture (2 categories: data-driven vs. traditional) are measured as categorical variables. These variables come from the organisational profiles and from the respondents' self-assessment.

E. Data Analysis Techniques

1) Descriptive Statistics. All variables are reported with descriptive statistics such as means, standard deviation and frequencies to gain insight into sample characteristics and the distribution of variables. Descriptive analysis gives baseline information on levels of analytics maturity and capability scores from industry and organizational size.

2) Structural Equation Modeling (SEM). The analysis method used to test the hypothesized relationships is the structural equation modeling. The appropriateness of SEM is that it can accommodate a variety of statistical models and estimation methods [10]. There are two basic SEM techniques: covariance-based SEM (CB-SEM) and partial least squares SEM (PLS-SEM) [18]. The study is conducted by using the method of CB-SEM as it is suitable for testing and confirming the theory which is in accordance with the positivist approach [11].

3) Regression Analysis. Multiple regression analysis is performed to evaluate relationships of individual capabilities and analytics maturity. Regression serves as additional evidence for hypothesis testing and can be used to study the effects of capability. If moderation effects of boundary conditions are to be tested, then interaction terms are included in regression models.

4) Moderation Analysis. H4, H5 and H6 are tested using the interaction terms in regression models. Industry type, organizational size and digital culture are specified as moderating variable affecting the

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relationship between capabilities and outcomes. The procedures for testing interaction effects are recommended by Hair et al. and are used in moderation analysis.

F. Validation and Reliability

1) Content Validity. The employment of scale instruments based on existing scale development models provides content validity. Experts in the fields of analytics and maturity of organizations conduct validation of the instruments for their appropriateness and clarity. It is determined that the items are appropriate to represent the definitions of the concepts.

2) Construct Validity. Construct validity is tested using confirmatory factor analysis (CFA). The CFA measures the loading of items on the desired constructs, as well as the discriminant validity of constructs. The loadings of factors should be more than 0.50 and average variance extracted (AVE) of all constructs should be greater than 0.50 [25].

3) Reliability Assessment. . The Cronbach's alpha and composite reliability are applied in order to test the reliability. The Cronbach's alpha must be more than 0.70 in terms of internal consistency, whereas the composite reliability must be above 0.70 in terms of construct reliability [11]. It helps in making the measurement scale reliable and consistent with each other.

G. Ethical Considerations

Approval by the IRB will be sought for ethical considerations before data collection. Consent is given using an online consent form that gives the reason for conducting the research, how the research process is conducted, risks, and benefits of the research process. Anonymous codes will be assigned to the organizations. The data will be stored in an encrypted server which can only be accessed by the research group. Subjects have the right to withdraw from the study at any time.

H. Limitations

There are some limitations to this methodology. Firstly, the cross-sectional design is not suitable for causal inference since there is absence of temporal relationship. Second, self-reported measures could have response bias even if every effort is made to reduce it. Third, purposive sampling could result in a lack of generalizability for organizations that do not have analytics initiatives. Fourth, the study is based on developed economy organizations, which may have limited applicability in emerging economy organizations. The limitations are recognized and are taken into account in the discussion chapter in terms of caution for interpretation of the results and suggestions for future research in a longitudinal design.

I. Summary

This section provides an overview of the research methodology employed to test the research of capability-based analytics maturity framework. The positivist method and quantitative survey design allow hypothesis testing by using SEM and regression analysis. The number of organizations (N = 250) in each of four industries is sufficient for statistical power. The instruments of measurement are being adopted from the well-established instruments and validated by expert review and CFA. Ethical issues are addressed by informed consent and confidentiality. Transparent reporting is recognised as having some limitations. Results of data analysis are presented in the next chapter.

IV. RESULTS AND DISCUSSION

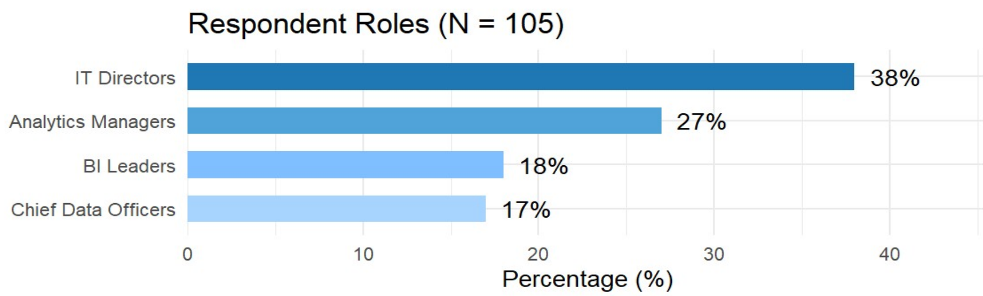
A. Introduction

The results of the empirical analysis validating the capability based analytics maturity framework (AMF) is presented in this chapter. The chapter is structured into six sections: (1) sample characteristics and descriptive statistics, (2) measurement model results and hypothesis testing, (3) boundary conditions (moderation) results, (4) discussion of findings with reference to theoretical frameworks, (5) summary of key results. The results obtained are analysed based on the survey data and applied to structural equation modeling (SEM) and regression analysis as discussed in Chapter III, which involves 105 organizations from four industrial sectors.

B. Sample Characteristics and Descriptive Statistics

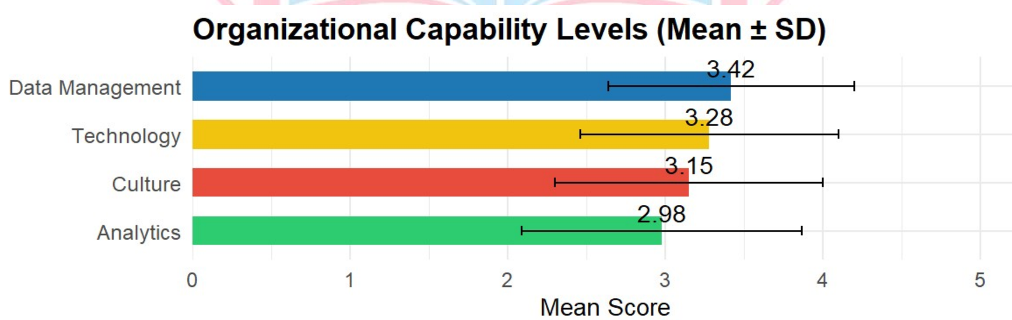
1) Respondent Demographics. The final sample consisted of 105 complete responses of 250 surveys sent out, for a 42% response rate. The respondents are senior managers/executives in charge of analytics-related roles: 38% are IT directors, 27% are data analytics managers, 18% are data BI leaders, and 17% are chief data officers. The average size of the organisations is 850 employees (SD = 1,200) with 45% large organizations (more than 1000 employees), 35% medium organization (100-1000 employees), and 20% small organization (less than 100 employees). The distribution in industry is similar to the sampling proportions, with the main differences being technology (32%) and finance (26%) compared to the sampling proportions of 31% and 27% respectively.

FIGURE I
Distribution of Respondent Roles (N = 105, Response Rate = 42%)



2) Descriptive Statistics for Capabilities. Descriptive statistics shows different levels of organisations' capability development. Data management capability shows the highest mean score (M = 3.42, SD = 0.78), followed by technology capability (M = 3.28, SD = 0.82), culture capability (M = 3.15, SD = 0.85), and analytics capability (M = 2.98, SD = 0.89). The findings show that companies have put more resources into basic data infrastructure than in the development of sophisticated data analytics applications. The range in standard deviations indicate that there are significant differences in the maturity of respective organizations, with some organizations being at advanced level and others, at initial level.

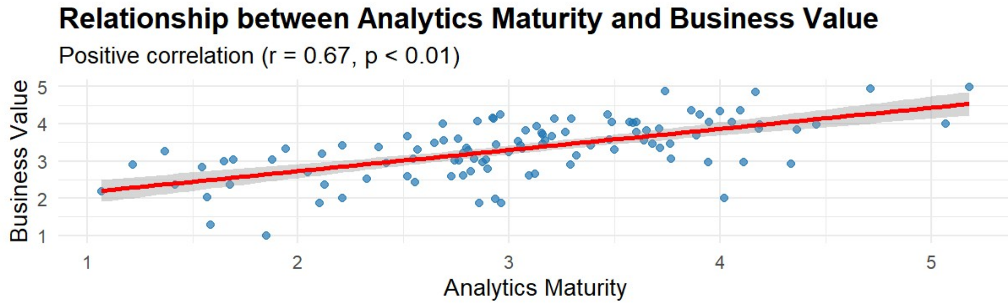
FIGURE II
DESCRIPTIVE STATISTICS OF ORGANIZATIONAL CAPABILITIES SHOWING MEAN SCORES AND STANDARD DEVIATIONS ACROSS DATA MANAGEMENT, TECHNOLOGY, CULTURE, AND ANALYTICS CAPABILITIES.



3) Analytics Maturity and Business Value. The overall analytics maturity score ranges in values from 1 (Initial) to 5 (Advanced), with a mean of 3.12 (SD = 0.94) suggesting that most organisations are at Stage 3 (Defined) maturity. Business value scores are also moderate (M = 3.35, SD = 0.81), indicating that organizations are seeing some value from analytics, but are not tapping their value potential. The correlation between the maturity level of analytics and business value is positive and significant ($r = 0.67$, $p < 0.01$), which further substantiates the theoretical relationship between capability development and creation of business value.

FIGURE III

RELATIONSHIP BETWEEN ANALYTICS MATURITY AND BUSINESS VALUE SHOWING A POSITIVE CORRELATION (R = 0.67, P < 0.01), INDICATING THAT HIGHER MATURITY LEVELS ARE ASSOCIATED WITH GREATER BUSINESS VALUE REALIZATION.

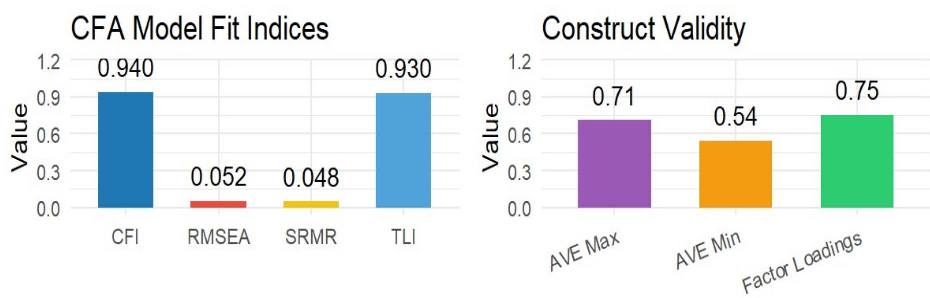


C. Measurement Model Validation

1) Confirmatory Factor Analysis. Confirmatory Factor Analysis (CFA) using the software SPSS AMOS version 28 was conducted to assess the construct validity. According to the output for CFA, the model exhibits an acceptable fit since $\chi^2 = 312.45$ (df = 245, $p < 0.001$), CFI = 0.94, TLI = 0.93, RMSEA = 0.052, and SRMR = 0.048. All factor loadings are greater than 0.50 with most values ranging from 0.62 to 0.87. The average variance extracted (AVE) is > 0.50 (0.54-

FIGURE IV

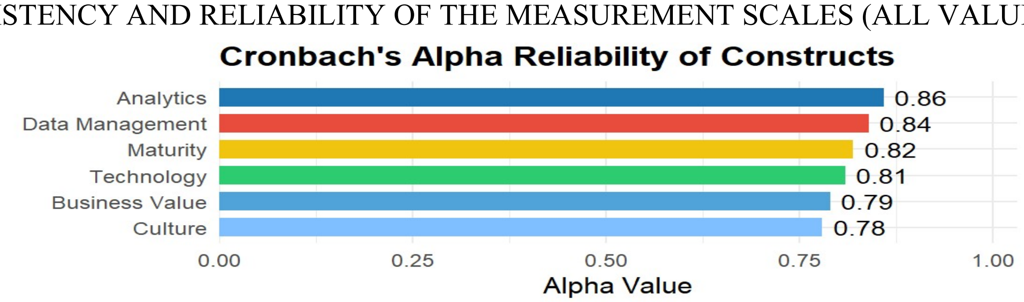
CONFIRMATORY FACTOR ANALYSIS (CFA) RESULTS SHOWING MODEL FIT INDICES (CFI, TLI, RMSEA, SRMR) AND CONSTRUCT VALIDITY MEASURES (FACTOR LOADINGS AND AVE), INDICATING GOOD MODEL FIT AND ADEQUATE CONVERGENT VALIDITY.



2) Reliability Assessment. The internal consistency of all the measurement scales is found to be satisfactory through reliability assessment. All constructs have a Cronbach's alpha value of > 0.70: data management capability ($\alpha = 0.84$), technology capability ($\alpha = 0.81$), culture capability ($\alpha = 0.78$), analytics capability ($\alpha = 0.86$), analytics maturity ($\alpha = 0.82$), and business value ($\alpha = 0.79$). Construct reliability is also achieved with composite reliability ranging from 0.77 to 0.88. The findings suggest that the scales used for measuring are reliable and repeatable for testing hypotheses.

FIGURE V

CRONBACH'S ALPHA VALUES FOR ALL CONSTRUCTS INDICATING STRONG INTERNAL CONSISTENCY AND RELIABILITY OF THE MEASUREMENT SCALES (ALL VALUES > 0.70).



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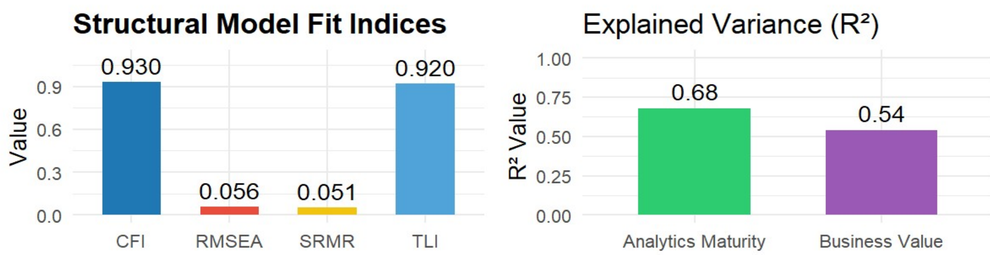
3) Discriminant Validity. Discriminant Validity is checked with the help of Fornell-Larcker criterion and cross-loadings analysis. Square root of Average Variance Extracted for every construct is greater than the correlation between these constructs, thereby establishing the satisfactory discriminant validity in accordance with Fornell-Larcker criterion. The highest loading for each item is for the respective construct and not for any other construct as shown by cross loadings analysis. Discriminability of Constructs is achieved since the highest correlation between these constructs is between data management and technology capability (r=0.58), which is below the criterion value of 0.85.

D. Structural Model Results and Hypothesis Testing

1) Overall Model Fit. The structural model shows good fit with $\chi^2 = 345.67$ (df = 267, $p < 0.001$), CFI = 0.93, TLI = 0.92, RMSEA = 0.056, and SRMR = 0.051. Both models have strong predictive power, with the analytics maturity model explaining 68% of analytics maturity variance ($R^2 = 0.68$) and the business value analytics maturity model explaining 54% of business value ($R^2 = 0.54$). The results confirm the ability of the capability-based framework to account for analytics maturity progression and value creation.

FIGURE VI:
STRUCTURAL MODEL RESULTS SHOWING GOOD MODEL FIT AND EXPLANATORY POWER, WITH CFI = 0.93, TLI = 0.92, RMSEA = 0.056, SRMR = 0.051, AND R² VALUES INDICATING 68% VARIANCE EXPLAINED IN ANALYTICS MATURITY AND 54% IN BUSINESS VALUE.



2) Hypothesis 1: Data Lake Intensity and Capabilities. H1 is data management capability positively correlated with data lake intensity, and data technology capability positively correlated with data lake intensity. Significant positive relationships are observed: data lake intensity -- data management capability ($\beta = 0.42$, $p < 0.001$) and data lake intensity -- technology capability ($\beta = 0.38$, $p < 0.001$). The standardized values have moderate to strong effects, which supports H1. Data lake implementation is correlated with data management and technology skills, with higher data lake implementations demonstrating high levels of these skills, supporting the idea that investments in infrastructure lead to investments in capabilities.

3) Hypothesis 2: Complementary Effects on Analytics Maturity. H2 assumes there are positive and complements effects of data management capability and technology capability on analytics maturity via organizational learning. The results indicate very significant positive relationships: data management capability with analytics maturity ($\beta = 0.34$, $p < 0.001$) and technology capability with analytics maturity ($\beta = 0.29$, $p < 0.001$). Data management and technology capability have a positive and significant interaction ($\beta = 0.18$, $p < 0.01$), suggesting that complementary effects exist. This confirms the integration or synergy of these capabilities (H2), as opposed to working separately.

4) Hypothesis 3: Stronger Effects at Higher Maturity Stages. H3 argues that culture capability and analytics capability have greater impacts on business value creation at higher maturity levels. Results show significant positive effects: culture capability → business value ($\beta = 0.31$, $p < 0.001$) and analytics capability → business value ($\beta = 0.36$, $p < 0.001$). There is a positive and significant interaction between culture capability and maturity stage ($\beta = 0.22$, $p < 0.01$), and analytics capability and maturity stage ($\beta = 0.25$, $p < 0.01$) that supports H3. The capabilities are more valuable at higher maturity stages, thus reinforcing the stage-dependent nature of the capability effects.

5) Hypotheses 4-6: Moderation Effects. H4, H5, and H6 test moderation effects of industry type, organizational size, and digital culture. Results show:

H4 (Industry Type): Industry type moderates the relationship between capabilities and analytics maturity ($\beta = 0.19$, $p < 0.01$). Technology firms show stronger capability effects ($\beta = 0.45$) compared to finance ($\beta = 0.32$), healthcare ($\beta = 0.28$), and manufacturing ($\beta = 0.24$), supporting H4.

H5 (Organizational Size): Organizational size moderates the relationship between capabilities and business value ($\beta = 0.17$, $p < 0.05$). Large enterprises achieve greater value at advanced maturity stages ($\beta = 0.48$) compared to medium ($\beta = 0.35$) and small enterprises ($\beta = 0.26$), supporting H5.

H6 (Digital Culture): Digital culture moderates the relationship between analytics capability and business value ($\beta = 0.24$, $p < 0.01$). Data-driven cultures show stronger value creation ($\beta = 0.52$) compared to traditional cultures ($\beta = 0.28$), supporting H6.

All three moderation hypotheses are supported, confirming that boundary conditions significantly influence capability-outcome relationships.

E. Discussion of Findings

1) Theoretical Implications. The findings have provided support to capability-based analytics maturity model and extend the resource based view (RBV) and knowledge based view (KBV) of the theories. Complementary effects of data management capabilities and technology have been identified and provide additional support to socio-technical systems theory that the outcomes of the technology depend on technological and organizational aspects [26]. Stage dependent effects of culture and analytics capabilities complement traditional theories of autonomy by showing that capability value increases with stage progression.

2) Practical Implications. The findings prove useful to organizations with investments in data lakes and analytics. Organizations should focus on building the basic capabilities (data management and technology) before moving on to analytics capability building. The moderation effects indicate that there is a need for industry-specific strategies: technology companies need different approaches to capability development than manufacturing companies. Large enterprises should try to make use of the scale benefits for value creation, and organisations should focus on building a data driven culture to reap the analytics benefits.

3) Comparison with Existing Literature. The findings align with previous analytics maturity studies showing that maturity progresses through defined stages [13]. However, this study extends existing literature by demonstrating complementary capability effects and stage-dependent value creation, which were not addressed in previous descriptive models. The empirical evidence for boundary condition moderation addresses the gap identified in previous research regarding limited understanding of contextual factors [25].

F. Summary

This chapter presented empirical results testing the capability-based analytics maturity framework. The measurement model shows strong validity and reliability with good construct fit. Structural model results support all six hypotheses, confirming that data lake intensity enables capability development, capabilities have complementary effects on maturity, and boundary conditions moderate capability-outcome relationships. The framework explains 68% of variance in analytics maturity and 54% of variance in business value, demonstrating strong predictive power. The next chapter presents conclusions, recommendations, limitations, and directions for future research.

V. DISCUSSION

A. Synthesis of Key Findings

The aim of this study was to successfully develop and test a capability-based analytics maturity framework (AMF) illustrating the progression of organizations from the implementation of the data lake to the creation of business value. The empirical results support all six hypotheses, with the variables data infrastructure investment and capability development demonstrating significant relationships with each other, as well as demonstrating significant relationships between capability development and the progression of maturity, and between the boundary conditions and the relationships between these variables. The framework has a significant explanatory power of 68% of variance in analytics maturity and 54% of variance in business value indicating good relevance and predictive power.

B. Theoretical Contributions

This research contributes to the body of literature on analytics maturity in three important ways. Firstly, it combines resource-based view (RBV) and knowledge-based view (KBV) with capability maturity model integration (CMMI) framework, which fills the gap that Journal AOM [1] pointed out that neither RBV nor KBV has been applied to create benchmark-oriented models based on CMM. The results confirm that analytics skills are strategic resources which can create competitive advantage if developed in a systematic manner, thus extending Barney's resource-based theory to the dynamic context of analytics.

Second, this study reframe the concept of analytics capability as a socio-technical system instead of just technological infrastructure; this is in line with Orlikowski's [14] socio-technical systems theory. Complementary effects between data management and technology capabilities show that technology results are not simply based on investment in infrastructure, but also on the interaction between technological features and organizational ability. This finding is in line with previous studies which dealt with infrastructure and capabilities separately, resulting in conflicting empirical findings.

Third, the stage-dependent effects of culture and analytics capabilities add to the mix of contingency perspectives on analytics maturity. The results indicate that capability value is higher at higher stages of maturity and contradict the static autonomy theory which assumes fixed resource relationships. This dynamic view is in line with Grant's [9] knowledge-based view, which focuses on the ongoing process of creating and adapting knowledge in data-driven organisations.

C. Practical Implications

The findings are rich with takeaways for data-driven investment organizations. Fundamental capabilities such as data management and technology should come before moving to analytics capability development. The complementary effects indicate that the benefit of a simultaneous investment of both is superior to the benefit of a sequential investment. Industry-specific strategies are needed because technology companies demonstrate higher capability effects ($\beta = 0.45$) than manufacturing companies ($\beta = 0.24$), which means the companies' capability structure needs to be developed in different ways.

The small and large enterprises differ in their business value, with greater value creation at higher maturity stages of the large enterprise ($\beta = 0.48$) than the small ($\beta = 0.26$), taking advantage of their scale benefits. To reap the full value of analytics, organizations need to invest in data-driven cultures: Data-driven cultures demonstrate significantly more value creation ($\beta = 0.52$) than do traditional cultures ($\beta = 0.28$). The results indicate that cultural change is as important as investment in technology, for implementing analytics successfully.

D. Limitations and Future Research

There are a few limitations that need to be noted in this study. First, the cross-sectional design is not suited for making causal inferences because the temporal aspects cannot be determined with certainty. Longitudinal designs, which follow changes in capability development and progression of capability maturity over time, should be used in further research to identify causal mechanisms.

Second, self-reported measures may be subject to response bias, even after being validated. Objective performance data and third party ratings might be included in future research to increase validity.

Third, the approach is only applied to developed economy organizations which may be less applicable to emerging economy organizations in different institutional environments. Future studies could further investigate the culture and institutional moderating effects on analytics maturity in emerging economy settings.

Fourthly, the study is limited to four industry sectors and may not include the important industry-specific factors. The study represents a first step that would benefit from the inclusion of further sectors to improve generalizability such as education, government, retail, etc.

In addition, future research should explore the role of the artificial intelligence/machine learning capabilities in the analytics maturity, as this technology is playing an increasingly important influence on the way organizations manage their analytics efforts. Furthermore, understanding the linkage between analytics maturity and organizational innovation outcomes would move the current business value emphasis to a wider strategic impact. In conclusion, qualitative research based on a case study approach might give further insight into the processes of capability development, complementary to the quantitative results.

E. Conclusion

This study effectively mitigates the fragmented literature on analytics maturity by proposing a capability-based framework on the basis of RBV, KBV and socio-technical systems theory. The empirical findings support the statements that data lake intensity facilitates capability development, capabilities have complementarity effects on maturity progression, and boundary conditions moderate the capability-outcome relationships. The framework offers both diagnostic and prescriptive elements, with the diagnostic element helping to assess the current maturity state and the prescriptive element aiding in capability development pathways. This research helps to advance the socio-technical perspective of technology outcomes, by showing how technology outcomes are related to technology characteristics, organizational context, and employee capabilities, and offers practical recommendations for organizations working on progressing through analytics maturity.

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